IMDB_Sentiment_Analysis

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1 IMDB Sentiment Analysis

By Neuromatch Academy

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[1]:

```
# Import needed libraries
import pandas as pd
import numpy as np
import re
import torch
import torchtext
from torch.utils.data import DataLoader, Dataset
from torchtext.data.utils import get_tokenizer
from torchtext.vocab import build_vocab_from_iterator
from torch.nn.utils.rnn import pad_sequence
from sklearn.model_selection import train_test_split

import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer, WordNetLemmatizer
```

[2]:

```
# Download necessary NLTK data files
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

[2]:

```
True
```

Loading dataset

[3]:

```python
# Import the dataset from google drive
from google.colab import drive
drive.mount('/content/drive')
df = pd.read_csv('/content/drive/My Drive/IMDBdataset.csv')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[4]:

```python
df.head()
```

[4]:

```
                                              review sentiment
0  One of the other reviewers has mentioned that …  positive
1  A wonderful little production. <br /><br />The…  positive
2  I thought this was a wonderful way to spend ti…  positive
3  Basically there's a family where a little boy …  negative
4  Petter Mattei's "Love in the Time of Money" is…  positive
```

[6]:

```python
texts = df['review'].tolist()
labels = df['sentiment'].tolist()
```

Preprocessing steps

[5]:

```python
# Text cleaning function
def clean_text(text):
    text = text.lower()  # Convert to lowercase
    text = re.sub(r'<.*?>', '', text)  # Remove HTML tags
    text = re.sub(r'[^\w\s]', '', text)  # Remove punctuation
    text = re.sub(r'\d+', '', text)  # Remove digits
    return text

# Tokenization function
def tokenize(text):
    return word_tokenize(text)

# Stop words removal function
def remove_stopwords(tokens):
    stop_words = set(stopwords.words('english'))
    return [word for word in tokens if word not in stop_words]

# Stemming function
def stem_tokens(tokens):
    stemmer = PorterStemmer()
    return [stemmer.stem(word) for word in tokens]

# Lemmatization function
def lemmatize_tokens(tokens):
    lemmatizer = WordNetLemmatizer()
    return [lemmatizer.lemmatize(word) for word in tokens]
```

```
def preprocess(text):
    text = clean_text(text)
    tokens = tokenize(text)
    tokens = remove_stopwords(tokens)
    tokens = lemmatize_tokens(tokens)
    return ' '.join(tokens)

def preprocess_and_tokenize(text):
    text = clean_text(text)
    tokens = tokenize(text)
    tokens = remove_stopwords(tokens)
    tokens = lemmatize_tokens(tokens)
    return tokens
```

[6]:
```
df['cleaned_review'] = df['review'].apply(preprocess)
df.head()
```

[6]:
```
                                              review sentiment  \
0  One of the other reviewers has mentioned that …  positive
1  A wonderful little production. <br /><br />The…  positive
2  I thought this was a wonderful way to spend ti…  positive
3  Basically there's a family where a little boy …  negative
4  Petter Mattei's "Love in the Time of Money" is…  positive

                                      cleaned_review
0  one reviewer mentioned watching oz episode you…
1  wonderful little production filming technique …
2  thought wonderful way spend time hot summer we…
3  basically there family little boy jake think t…
4  petter matteis love time money visually stunni…
```

Lets make an example

[8]:
```
sample_text = "I loved this movie! It was amazing, the acting was great and the␣
 ↪plot was very exciting."
print(sample_text)
print(preprocess(sample_text))
print(preprocess_and_tokenize(sample_text))
```

```
I loved this movie! It was amazing, the acting was great and the plot was very
exciting.
loved movie amazing acting great plot exciting
['loved', 'movie', 'amazing', 'acting', 'great', 'plot', 'exciting']
```

[9]:
```
preprocessed_tokens = [preprocess_and_tokenize(text) for text in texts]
```

Building vocabulary

[10]:

```
# Build vocabulary from the tokenized texts
from collections import Counter
def yield_tokens(data_iter):
    for tokens in data_iter:
        yield tokens

vocab = build_vocab_from_iterator(yield_tokens(preprocessed_tokens),␣
 ↪specials=["<unk>"])
vocab.set_default_index(vocab["<unk>"])
```

[11]:

```
words = Counter()
for s in preprocessed_tokens:
  for w in s:
    words[w] += 1

sorted_words = list(words.keys())
sorted_nums = list(words.values())
sorted_words.sort(key=lambda w: words[w], reverse=True)
sorted_nums.sort(reverse=True)
print(f"Number of different reviews in our dataset: {len(preprocessed_tokens)}")
print(f"Number of different tokens in our dataset: {len(sorted_words)}")
print("Top 100 tokens and their frequencies:")
print(sorted_words[:100])
print(sorted_nums[:100])
```

```
Number of different reviews in our dataset: 50000
Number of different tokens in our dataset: 203664
Top 100 tokens and their frequencies:
['movie', 'film', 'one', 'like', 'time', 'good', 'character', 'get', 'even',
'story', 'would', 'make', 'see', 'really', 'scene', 'much', 'well', 'people',
'great', 'bad', 'also', 'show', 'first', 'dont', 'way', 'thing', 'made',
'could', 'think', 'life', 'go', 'know', 'watch', 'love', 'many', 'seen',
'actor', 'two', 'plot', 'say', 'never', 'look', 'acting', 'end', 'little',
'best', 'year', 'ever', 'better', 'take', 'man', 'come', 'still', 'work',
'part', 'find', 'something', 'want', 'give', 'lot', 'back', 'director', 'im',
'real', 'guy', 'watching', 'doesnt', 'performance', 'didnt', 'play', 'woman',
'actually', 'though', 'funny', 'another', 'nothing', 'going', 'role', 'u',
'new', 'old', 'every', 'girl', 'cant', 'point', 'cast', 'world', 'fact',
'thats', 'quite', 'day', 'got', 'pretty', 'feel', 'minute', 'thought', 'seems',
'around', 'young', 'comedy']
[98839, 89766, 52616, 39736, 29359, 28582, 27539, 24395, 24264, 24204, 23974,
23527, 23469, 22856, 20667, 18874, 18607, 17963, 17769, 17654, 17471, 16864,
16827, 16607, 16515, 16051, 15399, 15126, 15065, 14381, 14263, 14047, 13666,
13352, 13254, 13090, 12997, 12920, 12881, 12842, 12826, 12561, 12397, 12317,
12296, 12286, 12263, 11620, 11041, 11024, 10986, 10856, 10649, 10400, 9965,
9940, 9809, 9771, 9678, 9577, 9282, 9025, 9004, 8989, 8925, 8913, 8862, 8803,
8786, 8661, 8632, 8351, 8333, 8307, 8174, 8161, 8066, 8039, 8017, 7953, 7860,
7854, 7495, 7476, 7337, 7289, 7269, 7248, 7212, 7210, 7179, 7175, 7153, 7153,
7143, 7061, 7039, 6975, 6949, 6913]
```

[12]:

```
print(sum(sorted_nums[:100]))
print(sum(sorted_nums))
print(sum(sorted_nums[:100])/sum(sorted_nums))
```

```
1476813
5923292
0.24932301159557896
```

interesting!

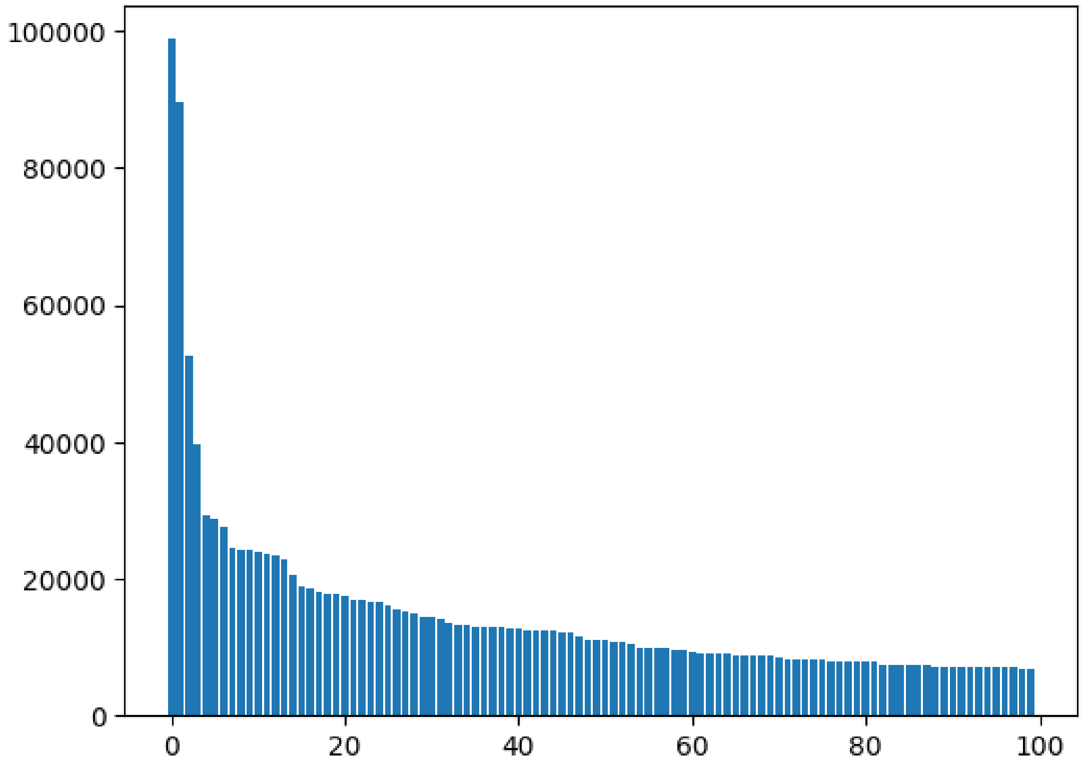
[13]:

```
print(sorted_nums[sorted_words.index("deep")])
print(sorted_nums[sorted_words.index("learning")])
```

```
1345
327
```

[14]:

```
import matplotlib.pyplot as plt
plt.bar(range(100), [words[w] for w in sorted_words[:100]])
plt.show()
```



Split the dataset

[7]:

```
from sklearn.model_selection import train_test_split

# Split the data
X_train_txt, X_test_txt, Y_train, Y_test =␣
 ↪train_test_split((df['cleaned_review']), df['sentiment'].apply(lambda x: 1␣
 ↪if x == 'positive' else 0).values
, test_size=0.5, random_state=42)
```

Now, lets vectorize the samples

[9]:

```
from sklearn.feature_extraction.text import TfidfVectorizer

# Initialize TF-IDF vectorizer
vectorizer = TfidfVectorizer(max_features=10000)

# Fit and transform the cleaned reviews
X_train = vectorizer.fit_transform(X_train_txt).toarray()
X_test = vectorizer.transform(X_test_txt).toarray()
```

[10]:

```
def check_nonzero_features(x):
  nonzero = x[x != 0]
  print("Number of nonzero features:" , len(nonzero))
  print((nonzero))
  # You can also get the index of nonzero features
  # print([index for index, value in enumerate(o != 0) if value])
```

[11]:

```
print(check_nonzero_features(X_train[0]))
```

```
Number of nonzero features: 135
[0.08308818 0.04954787 0.09966081 0.15298001 0.03016194 0.0441028
 0.04114457 0.0993238  0.03100172 0.16672422 0.0500792  0.04819476
 0.07609498 0.09340828 0.10378096 0.05355693 0.06496041 0.12017865
 0.08437068 0.0884021  0.06264701 0.04697297 0.20756193 0.06562026
 0.07594037 0.03092596 0.06370697 0.20250485 0.06984642 0.03951615
 0.06942714 0.04905622 0.08120401 0.05023807 0.05603505 0.06828883
 0.07042808 0.08947972 0.1785134  0.08132123 0.04280841 0.03326436
 0.05714294 0.08005111 0.19306225 0.05980858 0.0437039  0.05325442
 0.03914241 0.0637653  0.08167956 0.03203274 0.09280815 0.04407826
 0.16728427 0.10828506 0.13270489 0.0484436  0.06090108 0.0787713
 0.06179373 0.18743884 0.1553338  0.03313255 0.02241406 0.2036772
 0.04434458 0.05043952 0.09821368 0.05497301 0.06984642 0.08947972
 0.08350134 0.0729636  0.08970676 0.03795311 0.11530888 0.0492395
 0.0198199  0.09867193 0.0635623  0.0487862  0.06115992 0.03304544
 0.06139994 0.04556621 0.04778516 0.0679176  0.07395417 0.06099459
 0.04996135 0.15446771 0.08760181 0.06716805 0.09867193 0.05586211
 0.08378451 0.03938035 0.09041351 0.05283675 0.06561037 0.09371942
 0.0776669  0.06582515 0.05468531 0.04963329 0.06538536 0.10694764
 0.05406106 0.10724432 0.05763645 0.14346728 0.0458381  0.0892567
 0.08266091 0.0504091  0.05703966 0.12309235 0.05703966 0.05928567
 0.03126053 0.03927107 0.14313928 0.04368607 0.04366826 0.076173
 0.05592472 0.18284417 0.0358955  0.07042808 0.02914399 0.04906532
 0.09867193 0.05249749 0.04287508]
None
```

[12]:
```
del X_train_txt
del X_test_txt
```

[13]:
```
import gc
gc.collect()
```

[13]:
```
0
```

2 Implementation

Logistic Regression

[14]:
```
from sklearn.linear_model import LogisticRegression
LR_model = LogisticRegression(solver='saga')
LR_model.fit(X_train, Y_train)
```

[14]:
```
LogisticRegression(solver='saga')
```

[15]:
```
from sklearn.metrics import classification_report, accuracy_score
Y_pred_LR = LR_model.predict(X_test)
print(classification_report(Y_test, Y_pred_LR))
LR_acc = accuracy_score(Y_test , Y_pred_LR)
print(LR_acc)
```

```
              precision    recall  f1-score   support

           0       0.90      0.87      0.88     12483
           1       0.87      0.90      0.89     12517

    accuracy                           0.88     25000
   macro avg       0.89      0.88      0.88     25000
weighted avg       0.89      0.88      0.88     25000

0.88492
```

Multi Layer Perceptron

[16]:
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers
```

```python
MLP_model = Sequential()
MLP_model.add(Dense(128, input_dim=X_train.shape[1], activation='relu',␣
 ↪kernel_regularizer=regularizers.l2(0.001)))
MLP_model.add(Dropout(0.5))
MLP_model.add(Dense(64, activation='relu', kernel_regularizer=regularizers.l2(0.
 ↪001)))
MLP_model.add(Dropout(0.2))
MLP_model.add(Dense(32, activation='relu', kernel_regularizer=regularizers.l2(0.
 ↪0001)))
MLP_model.add(Dense(1, activation='sigmoid'))

MLP_model.compile(loss='binary_crossentropy',
              optimizer=Adam(learning_rate=0.004),
              metrics=['accuracy'])

history = MLP_model.fit(X_train, Y_train,
                    epochs=7,
                    batch_size=32,
                    validation_split=0.2,
                    verbose=1)
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Epoch 1/7
625/625               22s 32ms/step -
accuracy: 0.7711 - loss: 0.7425 - val_accuracy: 0.8588 - val_loss: 0.7699
Epoch 2/7
625/625               15s 25ms/step -
accuracy: 0.8608 - loss: 0.7778 - val_accuracy: 0.8634 - val_loss: 0.7666
Epoch 3/7
625/625               16s 25ms/step -
accuracy: 0.8573 - loss: 0.7883 - val_accuracy: 0.8548 - val_loss: 0.7829
Epoch 4/7
625/625               21s 25ms/step -
accuracy: 0.8658 - loss: 0.7720 - val_accuracy: 0.8604 - val_loss: 0.7483
Epoch 5/7
625/625               20s 25ms/step -
accuracy: 0.8661 - loss: 0.7628 - val_accuracy: 0.8590 - val_loss: 0.7468
Epoch 6/7
625/625               20s 25ms/step -
accuracy: 0.8679 - loss: 0.7343 - val_accuracy: 0.8626 - val_loss: 0.7171
Epoch 7/7
625/625               21s 25ms/step -
accuracy: 0.8648 - loss: 0.7313 - val_accuracy: 0.8426 - val_loss: 0.7541
```

[17]:

```
test_loss, test_accuracy = MLP_model.evaluate(X_test, Y_test, verbose=0)
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
Test Accuracy: 0.8420
```

Convolutional Neural Network

[18]:

```
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense,␣
 ↪Dropout
from tensorflow.keras.optimizers import Adam

# Reshape X_train to fit the input shape of Conv1D
X_train_cnn = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)

CNN_model = Sequential()
CNN_model.add(Conv1D(32, 5, activation='relu', input_shape=(10000, 1)))
CNN_model.add(MaxPooling1D(pool_size=2))
CNN_model.add(Conv1D(64, 5, activation='relu'))
CNN_model.add(MaxPooling1D(pool_size=2))
CNN_model.add(Flatten())
CNN_model.add(Dense(128, activation='relu'))
CNN_model.add(Dropout(0.5))
CNN_model.add(Dense(1, activation='sigmoid'))
CNN_model.compile(optimizer=Adam(learning_rate=0.001),␣
 ↪loss='binary_crossentropy', metrics=['accuracy'])
CNN_model.fit(X_train_cnn, Y_train, epochs=2, batch_size=32, validation_split=0.
 ↪2)
```

```
/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Epoch 1/2
625/625             655s 1s/step -
accuracy: 0.7692 - loss: 0.4644 - val_accuracy: 0.8642 - val_loss: 0.3086
Epoch 2/2
625/625             653s 997ms/step -
accuracy: 0.8977 - loss: 0.2492 - val_accuracy: 0.8734 - val_loss: 0.2980
```

[18]:

```
<keras.src.callbacks.history.History at 0x79a9dd25f910>
```

[19]:

```
# Evaluate the model
X_test_cnn = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)
```

```
loss, accuracy = CNN_model.evaluate(X_test_cnn, Y_test, verbose=2)
print(f'Test Accuracy: {accuracy:.4f}')
```

```
782/782 - 128s - 164ms/step - accuracy: 0.8721 - loss: 0.3045
Test Accuracy: 0.8721
```

Recurrent Neural Nrtwork

[20]:

```
# Reshape the data to have time steps and features per time step
sequence_length = 1
num_features = 10000

X_train_RNN = X_train.reshape((25000, sequence_length, num_features))
X_test_RNN = X_test.reshape((25000, sequence_length, num_features))

import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense
from tensorflow.keras.optimizers import Adam

RNN_model = Sequential()
RNN_model.add(SimpleRNN(400, input_shape=(1, 10000), return_sequences=False))
RNN_model.add(Dense(1, activation='sigmoid'))
RNN_model.compile(optimizer=Adam(learning_rate=0.0001),␣
  ↪loss='binary_crossentropy', metrics=['accuracy'])
RNN_model.fit(X_train_RNN, Y_train, epochs=4, batch_size=32, validation_split=0.
  ↪2)
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(**kwargs)
```

```
Epoch 1/4
625/625              44s 67ms/step -
accuracy: 0.7467 - loss: 0.6272 - val_accuracy: 0.8682 - val_loss: 0.4099
Epoch 2/4
625/625              41s 65ms/step -
accuracy: 0.8939 - loss: 0.3503 - val_accuracy: 0.8850 - val_loss: 0.3005
Epoch 3/4
625/625              41s 65ms/step -
accuracy: 0.9192 - loss: 0.2457 - val_accuracy: 0.8904 - val_loss: 0.2714
Epoch 4/4
625/625              41s 65ms/step -
accuracy: 0.9348 - loss: 0.1971 - val_accuracy: 0.8902 - val_loss: 0.2667
```

[20]:

```
<keras.src.callbacks.history.History at 0x79aa16fc3b20>
```

[21]:

```
loss, accuracy = RNN_model.evaluate(X_test_RNN, Y_test, verbose=2)
print(f'Test Accuracy: {accuracy:.4f}')
```

```
782/782 - 8s - 11ms/step - accuracy: 0.8906 - loss: 0.2647
Test Accuracy: 0.8906
```

Long Short-Term Memory

[22]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout

sequence_length = 1
num_features = 10000

X_train_LSTM = X_train.reshape((25000, sequence_length, num_features))
X_test_LSTM = X_test.reshape((25000, sequence_length, num_features))

LSTM_model = Sequential()
LSTM_model.add(LSTM(300, input_shape=(sequence_length, num_features),␣
 ↪return_sequences=False))
LSTM_model.add(Dropout(0.5))
LSTM_model.add(Dense(1, activation='sigmoid'))
LSTM_model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])
LSTM_model.fit(X_train_LSTM, Y_train, epochs=5, batch_size=32,␣
 ↪validation_split=0.2)
```

```
Epoch 1/5
625/625             188s 295ms/step -
accuracy: 0.7962 - loss: 0.4936 - val_accuracy: 0.8880 - val_loss: 0.2691
Epoch 2/5
625/625             209s 307ms/step -
accuracy: 0.9313 - loss: 0.1850 - val_accuracy: 0.8810 - val_loss: 0.2994
Epoch 3/5
625/625             186s 297ms/step -
accuracy: 0.9585 - loss: 0.1228 - val_accuracy: 0.8682 - val_loss: 0.3585
Epoch 4/5
625/625             206s 304ms/step -
accuracy: 0.9723 - loss: 0.0853 - val_accuracy: 0.8584 - val_loss: 0.4466
Epoch 5/5
625/625             190s 304ms/step -
accuracy: 0.9820 - loss: 0.0627 - val_accuracy: 0.8548 - val_loss: 0.5373
```

[22]:

```
<keras.src.callbacks.history.History at 0x79aa2892b520>
```

[23]:

```
loss, accuracy = LSTM_model.evaluate(X_test_LSTM, Y_test, verbose=2)
print(f'Test Accuracy: {accuracy:.4f}')
```

```
782/782 - 21s - 27ms/step - accuracy: 0.8598 - loss: 0.5026
```

```
Test Accuracy: 0.8598
```

BERT

[ ]:

```python
from transformers import AutoTokenizer, AutoModelForSequenceClassification
import torch
```

[ ]:

```python
model_name = "distilbert-base-uncased-finetuned-sst-2-english"
tokenizer = AutoTokenizer.from_pretrained(model_name)
model = AutoModelForSequenceClassification.from_pretrained(model_name)
```

[ ]:

```python
def analyze_sentiment(review):
    inputs = tokenizer(review, return_tensors="pt", truncation=True,␣
 ↪padding=True, max_length=512)
    with torch.no_grad():
        outputs = model(**inputs)
    logits = outputs.logits
    probabilities = torch.nn.functional.softmax(logits, dim=-1)
    predicted_class = torch.argmax(probabilities, dim=-1).item()
    labels = ["negative", "positive"]
    predicted_label = labels[predicted_class]
    return predicted_label
```

[ ]:

```python
sample_data = df.sample(5000)
y_pred = sample_data['review'].apply(analyze_sentiment)
y = sample_data['sentiment']
accuracy = (y_pred == y).mean()
print("Average Accuracy by BERT uncased model:", accuracy)
```

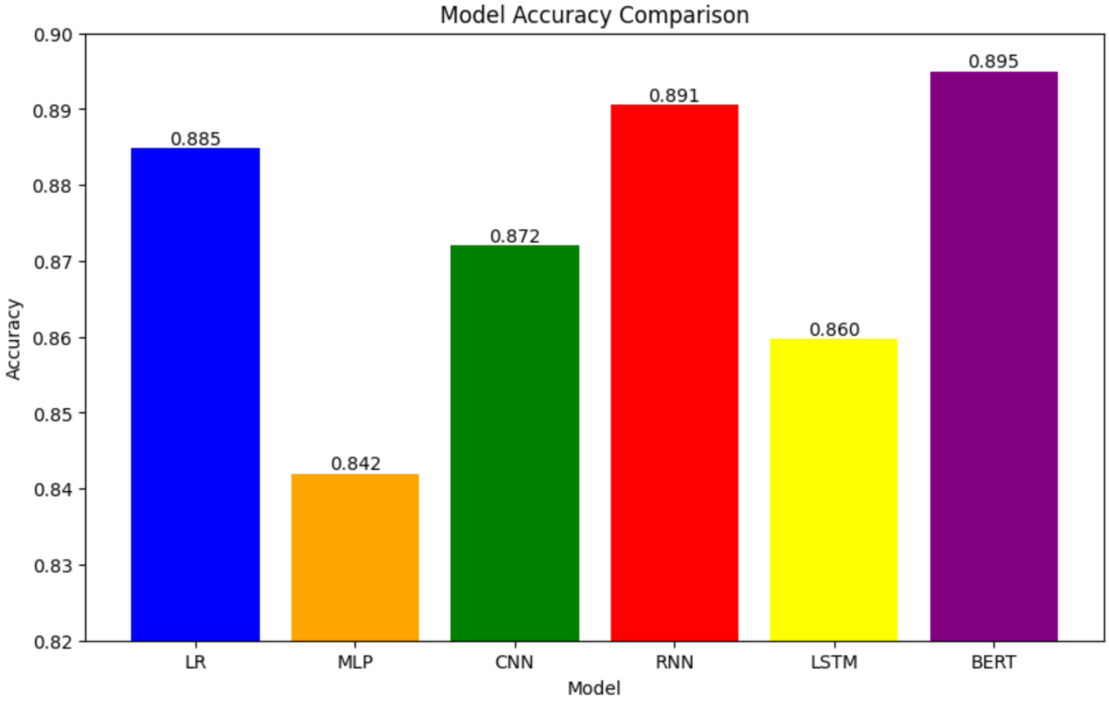
```
Average Accuracy by BERT uncased model: 0.895
```

Comparison

[25]:

```python
import matplotlib.pyplot as plt
data = {
    'Model': ['LR' , 'MLP', 'CNN' , 'RNN' , 'LSTM' , 'BERT'],
    'Accuracy': [0.88492, 0.8420, 0.8721, 0.8906, 0.8598, 0.8950]
}

# Bar Plot
plt.figure(figsize=(10, 6))
plt.bar(data['Model'], data['Accuracy'], color=['blue' , 'orange' , 'green' ,␣
 ↪'red' , 'yellow' , 'purple'])
for index, value in enumerate(data['Accuracy']):
    plt.text(index, value + 0.0005, f'{value:.3f}', ha='center')
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.title('Model Accuracy Comparison')
plt.ylim(0.82, 0.90)
plt.show()
```


Model Accuracy Comparison
Accuracy
0.90
0.89
0.88
0.87
0.86
0.85
0.84
0.83
0.82
0.885
0.842
0.872
0.891
0.860
0.895
LR
MLP
CNN
RNN
LSTM
BERT
Model